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Economic flourishing and floundering in emerging adulthood

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DEDICATION

To Rebecca, my best friend and favorite emerging adult.

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ABSTRACT

The primary purpose of this study is to analyze patterns of family and human capital in emerging adulthood in a latent profile analysis framework and to determine if group membership has implications for economic and financial flourishing and floundering via a relationship with positive financial behavior. By employing latent profile analysis, a multidimensional understanding of capital in emerging adulthood is explored and its importance in affecting key financial behaviors is evaluated. Indicators for the latent profile analysis include measures of parental financial support, financial knowledge, work experience, and higher education experiences—key life determinants following high-school graduation and between ages 18-23. The sample is 333 emerging adults from the Flourishing Families Studies (Waves 1-10 inclusive).

Results of the latent profile analysis indicated that a four-profile model provides the best fit for the sample. Each of the four profiles were defined by levels of parental financial support that were exclusive to that profile. The profiles were labeled Moderate High Support, High Support, Low Support, and Moderate Low Support. Evidence of variation in work and higher education experiences were found between latent profiles while evidence of differentiation in financial knowledge was not supported. Wald chi-square tests and ordinary least squares regression demonstrated differences by profile in positive financial behavior enactment. Future lines of research and implications for the financial education and parenting of emerging adults are discussed in light of study findings.

CHAPTER 1. INTRODUCTION

Life as an emerging adult is characterized by a diversity of individual goals, behaviors, and decisions that are often influenced by the availability of financial support during this developmental period and the socioeconomic position of the family of origin (Arnett, 2014; Swartz, 2008). This diversity extends into the economic life of emerging adults which encompasses education, employment, and financial experiences. The present study conceptualizes emerging adulthood as a life period in which important *capital* development takes place within experiences in education and employment. At the same time, emerging adults have developed some level of knowledge of the financial world and require financial support either from their own earnings or from some other source in order to meet their life goals. Many emerging adults receive financial or material support from their parents well into their twenties, while others become financially independent earlier in adulthood (Bea & Yi, 2018). Within this study, parental financial support, financial knowledge, work experience, and higher education experience are examined as capital in emerging adulthood.

This study uses a person-centered approach to identify a multidimensional understanding of capital in a sample of emerging adults ages 18 to 23 and shows the importance of different configurations of capital in affecting key financial behaviors. Specifically, parental financial support, financial knowledge, work experiences, and higher education experiences are used to discover latent patterns of capital. Additionally, how these latent profiles are associated with financial management behaviors, such as budgeting and saving, is examined in order to explore ways that emerging adults may be financially and economically flourishing or floundering.

Flourishing or Floundering?

The concepts flourishing and floundering have been used to describe emerging adults in a number of contexts. Nelson and Padilla-Walker (2013) reviewed literature that indicates flourishing in emerging adulthood corresponds with exploring and internalizing positive values, engaging in prosocial behaviors, and using media and technology for positive ends. Meanwhile in their review, emerging adults who are characterized as floundering had internalizing problems, externalizing problems, or engaged in various risk behaviors.

Researchers interested in employment patterns following completion of educational degrees have also been interested in categorizing emerging adults as flourishing or floundering. Osterman (1980) used the term *floundering* to describe young adults who frequently changed jobs or fluctuated into and out of the labor force. Heckman (1994), on the other hand, in his examination of young adults who frequently switched between low skill, low wage jobs described his sample as *searching*, a process that could lead to optimal matching between workers and job opportunities. Hamilton and Hamilton (2006) note that the interpretations of floundering and searching became conflicting concepts among economists and labor market researchers. They proposed:

> One way out of the argument between searching and floundering is to disaggregate the population. It seems plausible that some emerging adults move purposefully through their early work experience while others get bogged down by it. The challenge is to distinguish those who are following productive career paths from those who are not, to identify their characteristics, and to compare their relative proportions in the population (p. 266).

Family and developmental researchers also propose studying group differences in phenomena that could be potentially helpful or harmful for emerging adults. For example, Swartz (2008) discusses family material and social support to emerging adult children as a net positive for emerging adults but also acknowledges a need to investigate what forms and amounts of family support might diminish particular types of emerging adults' success and development.

This study aims to examine emerging adult flourishing and floundering in an economic and financial context. Analyzing who is economically flourishing or floundering from a person-centered methodology allows for the exploration of diversity in what it means to be doing well and doing poorly economically, and can uncover the possibility that there are multiple paths for floundering and/or multiple paths for flourishing. A person-centered classification model, like latent profile analysis, is an appropriate exploratory method to investigate how different patterns of financial support from parents, financial knowledge, work experience, and higher education may explain between-group heterogeneity across capital resources and within-group similarity.

In order to better understand which groups of emerging adults are financially flourishing or floundering, positive financial behavior enactment was examined for each pattern of emerging adult capital. It is widely believed by personal finance researchers and educators that the financial behaviors and habits that are developed in emerging adulthood will persist into later adulthood (Shim, Barber, Card, Xiao, & Serido, 2010). Additionally, financial behaviors in this life stage have been linked to both negative and positive outcomes, such as financial distress (Gutter and Copur, 2011); financial satisfaction (Xiao, Chen, & Chen, 2014); and academic performance, academic satisfaction, and overall life satisfaction (Xiao, Tang, & Shim, 2009). Furthermore, Huston (2010) directly links levels of general and specific human capital, such as financial literacy and knowledge, to financial behavior enactment in a model of financial well-being.

This study takes advantage of a unique dataset, the Flourishing Families Project, that not only contains educational and employment data for a cohort of emerging adults, but also a number of personal finance measures. Unlike most studies of emerging adults, which only consist of college students, the Flourishing Families Project allows for the inclusion of emerging adults who did not attend college and some who did not complete high school. Thus, it is possible to examine flourishing and floundering in a more heterogeneous emerging adult sample. It is also possible to include measures of family socioeconomic status.

Thesis Organization

This thesis follows the traditional format and is presented in five chapters, with this chapter serving as the introduction. Chapter 2 presents the theoretical and methodological frameworks, discusses relevant literature, and details this study's conceptual model and research questions. In chapter 3, research methods and the analytical plan are discussed. Results of the latent class analysis and regression analyses are displayed in chapter 4. Finally, chapter 5 provides a discussion of results, implications of the findings, and study limitations.

CHAPTER 2. REVIEW OF THEORY AND LITERATURE

Theoretical Frameworks

Emerging Adulthood

Emerging adulthood may be described as a human developmental period that follows adolescence and precedes more settled and enduring forms of adulthood. Although the boundaries of emerging adulthood are best determined by lifestyle and psychological factors (Arnett, 2000), most of the related research examines emerging adulthood beginning at age eighteen and extending through the twenties and sometimes into the early thirties (Arnett, 2014). Arnett (2006) names five common features of emerging adulthood, including identity exploration, instability, being self-focused, feeling *in-between* adolescence and adulthood, and a belief in possibilities. However, Arnett also names a sixth feature of emerging adulthood: heterogeneity. He calls attention to closely examining subgroup and individual differences when examining developmental trajectories and life transitions of emerging adults. In modern economies, emerging adults face a great amount of diversity for short- and long-term employment options, educational opportunities, and engagement in the financial marketplace.

Psychologists and sociologists recognized that for economically developed countries there was a shift in the latter half of the twentieth century in the amount of time it took for people to transition from adolescence to adult roles (Furstenberg, 2010; Furstenberg, 2015; Settersten, 2007). Arnett (2014) specifically cites the technological revolution of the late twentieth century and fewer manufacturing jobs as the impetus for the prolonged period between adolescence and adulthood; because of these factors, it became difficult for those without college degree to find high paying, full-time employment. Thus, enrolling in college or a vocational program became a common way for emerging adults to gain needed knowledge and skills to demonstrate their qualifications for full-time employment as well as a way to explore their interests and identities. Settersten and Ray (2010a, 2010b) point out that financial support from parents is necessary for many emerging adults to delay entry into the workforce in order to pursue higher education because financial aid is limited and a social safety net for emerging adults is non-existent in many modern economies.

Theories of Capital

Within the social sciences, the term capital has come to mean both tangible and intangible resources that individuals can utilize to be productive and to inform decision-making (Côté & Schwartz, 2002). Various forms of social capital (e.g. social networks, cultural norms, inherited wealth) have been theorized and studied as ways that socioeconomic advantage and disadvantage are transferred from parents to children and within organizations (Bourdieu 1984; Bengtson et al. 2002; Coleman, 1988; Lareau, 2003). The current study considers capital that flows from the family and capital held by the individual.

Family capital. Family capital is all of the material, financial, social, and cultural resources that one or more family members (often parents or grandparents) transfer or invest in another family member to provide that family member (often a child) with some type of advantage (Swartz 2008, 2009). Parental financial support to emerging adults is a widely researched way that parents provide capital to their children. Over the past several decades, the number of well-paying jobs that require a college degree, and in many cases an advanced college degree, have increased substantially (Cook & Furstenberg, 2002; Settersten, 2007; Gitelson & McDermott 2006). Concurrent with postsecondary education becoming necessary to acquire employment that provides a living wage, the cost of college has also dramatically increased, and non-credit forms of financial aid have become increasingly scarce (College Board, 2015; Johnstone & Marcucci, 2010; Mitchell, Leachman, & Masterson, 2016). It has also been difficult for college students to find adequate part-time employment to provide enough money to meet the gap between the financial aid they receive and their remaining school and living expenses (Carnevale, Smith, Melton, & Price, 2015). Thus, parents are often relied upon to provide financial assistance, and emerging adults from lower-income families often fare less well.

Common types of financial support that parents provide to their emerging adult children include providing funding for postsecondary education, subsidizing housing costs away from the parental home, co-residence in the parental home, and help paying basic living expenses, including necessities such as transportation and insurance (Aquilino, 2006). Between 2010 and 2015, an estimated 58% to 66% of U.S. parents with a college-going child between the ages of 18 and 23 reported paying for at least some college costs out of income or assets, and an estimated 10% to 13% of parents reported borrowing to fund at least part of a child's college expenses (Sallie Mae, 2015). Housing is another important area where parents provide financial support. A nationally representative study in the U.S., found that 48% of parents provided financial support for rent or utilities (Wightman, Schoeni, & Robinson, 2012). Without these forms of financial support, it is difficult for emerging adults to take important economic steps to get ahead. One study of young adults aged 22 to 30 found that, of those who did not finish a college degree, 58% had no family financial support; 63% of individuals who did complete an undergraduate degree had family financial support (Johnson & Rochkind, 2009).

There is also variation in parental financial support by race and ethnicity. Monetary subsidies are far more common among white families whereas co-residence is more common among Black and Latino families (Berry, 2006; Lee & Aytac, 1998; Rosenzweig & Wolpin, 1993; Sarkisian, Gerena, & Gerstel, 2006). In general, across racial and ethnic groups, parents with college degrees that have higher incomes, have accumulated more wealth, and have fewer children provide financial transfers to their emerging adult children in higher amounts and at more frequent intervals (Downey, 1995; Fingerman et al., 2015; Goldscheider & Goldscheider, 1991; Henretta, Grundy, & Harris, 2002; Henretta, Wolf, Van Voorhis, & Soldo, 2012; Hogan, Eggebeen, & Clogg, 1993; Lee & Aytac, 1998; Schoeni, 1997; Schoeni & Ross, 2005).

Human capital. A person's human capital consists of all the skills, abilities, knowledge, capabilities, and qualifications held by that individual that allow him/her to be productive in the labor force and in society at large (see Becker, 1962; Schuller, 2001; Schultz, 1961). Within the field of personal finance, there is growing interest about how a person's human capital influences financial behavior, ability to save and invest, and overall well-being (Delavande, Rohwedder, & Willis, 2008; Finke & Huston, 2016).

Schooling is one of the primary ways in which individuals invest in their own human capital and signal their qualifications in the labor market (Becker, 1962; Lanzi, 2007). In modern, information-based economies, pursuit of higher education is seen as essential for many young people, and many initiatives have been implemented to help increase access and preparedness for higher education. There are generally both economic and personal benefits for attending college and earning a degree. Abel and Dietz (2014) found that between 1970 and 2013, those with a bachelor's degree earned on average 56% more per year than those with only a high school diploma, while those with an associate's degree earned around 21 percent more per year than those with only a high school diploma. College can also provide opportunities for emerging adults to explore various career and social opportunities, build networks of friends and colleagues, and provides a period of moratorium in which emerging adults can focus on developing their own identity in the socioeconomic world (Settersten & Ray, 2010a; Arnett, 2015).

Some economists, sociologists, and developmental scholars who study youth employment hold the view that work experience during adolescence and the early twenties can be beneficial, especially when work is integrated with or viewed as part of educational opportunities (Hamilton & Hamilton, 2006; Mortimer, 2010). Multiple studies have found beneficial outcomes for college students who hold part-time, on-campus jobs, including higher persistence, higher academic achievement, and institutional integration (Beeson & Wessel, 2002; Cheng & Alcantara, 2007; Pike, Kuh, & Massa-McKinley, 2008). However, some research indicates that college students who regularly work more than 20 hours per week during the academic year are more likely to drop out of college (Bozick, 2007). Internships and summer jobs that expose adolescents and emerging adults to career possibilities provide opportunities to learn about multiple types of work, discover what types of work are personally interesting or satisfying, and develop social networks (Murphy, Blustein, Bohling, & Platt, 2010).

Financial literacy is a particular type of human capital that is thought to impact financial habits, practices, and decision making (Finke & Huston, 2016). Financial literacy is the ability to process economic information and is dependent on a person's stock of financial knowledge and numeracy (Lusardi & Mitchell, 2014). One of the most common ways to assess financial literacy is through sets of questions that ask respondents to apply their financial knowledge (see Lusdardi & Mitchell, 2008, 2011). Huston (2010) proposed a conceptual framework that links human capital to financial outcomes. In particular, financial literacy is included as a form of human capital in this model. It is theorized that endowed and attained human capital influence personal finance behaviors which in turn are related to financial well-being. Huston included family, culture, economic conditions, time preferences, and behavioral biases as factors that could also influence financial behaviors and well-being alongside the impact of human capital.

The Current Study

The goal of this study is to detect naturally occurring patterns of family and human capital among a sample of emerging adults by using a person-centered research approach and examining how different capital configurations relate to emerging adult financial behaviors. Person-centered methodologies emphasize understanding patterns of individual behaviors and characteristics; they aim to identify distinct subgroups within a population (Bergman & Magnusson, 1997; Bergman, Magnusson, & El-Khouri, 2003). Person-centered methodologies are particularly useful for understanding interindividual developmental differences (von Eye & Bogat, 2006). This study uses latent profile analysis, a subtype of latent class analysis, to explore how subpopulations in a heterogeneous sample contain individuals who are similar within subpopulations and how these subpopulations differ from each other (Collins & Lanza, 2010,).

The present study conceptualizes capital in emerging adulthood as an unobserved variable that can be inferred from parental financial support received, financial knowledge, work experience, and higher education experience. Parental financial support serves as an important source of start-up capital for many emerging adults, so it is important to consider for this stage of development. Financial knowledge questions are used to measure emerging adults' financial literacy. Work experience may function not only as a way for emerging adults to financially support themselves, but may also provide experiences in the larger economy to learn how to manage the money they are earning. Higher education experience provides emerging adults opportunities to increase their overall knowledge base, gain career skills, and develop social networks. This study also connects the concept of unobserved, latent capital configurations in emerging adulthood to positive financial behavior enactment. Figure 1 displays this study's conceptual model which depicts a relationship between latent capital configurations and financial behaviors.

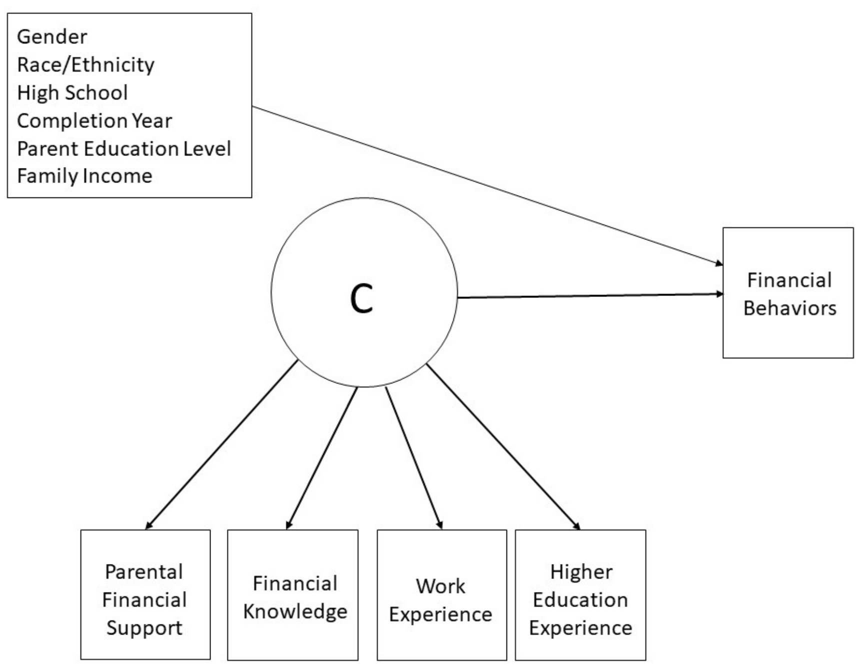

Figure 1. Latent class model of emerging adult capital and the relationship to financial behaviors.

Research Questions

Research questions for this study are presented below. Each of the two research questions are followed by a discussion of literature that points toward possible findings of the latent profile analysis and analysis of the relationship of latent profiles to financial behavior.

1. *How do emerging adults differ across dimensions of family and human capital?*

The aim of the first research question is to explore the heterogeneity of family and human capital. Within an emerging adult sample, latent profile analysis is employed with continuous measures of family financial support, financial knowledge, employment experience, and higher education experience serving as indicators of family and human capital.

Only a handful of empirical studies have examined how financial support from parents, financial literacy, work experience, or higher education combine within individuals. Bea and Yi (2018) found that emerging adults parental financial support trajectories from the age 18 to 27 fell into four types: consistently independent from parents, quickly independent from parents, gradually independent, and consistently supported. Findings from this study demonstrate that many emerging adults move into financial independence early in life. Xiao, Chatterjee, & Kim (2014) found that individuals in college perceived themselves to be more financially dependent on their parents than emerging adults who had graduated from college or who had never attended college. Mitchell and Syed (2015) compared work experience trajectories from age 14 to 30 between emerging adults who graduated from college and those who never attended college. Emerging adults who never attended college were more likely to work more hours during high school and immediately post high school compared to college graduates. Among a sample of young adults, de Bassa Scheresberg (2013) found that financial knowledge scores were substantially lower for individuals who had never gone to college compared to those who attended college.

Based on these research findings, the latent profile analysis is likely to yield at least three latent profiles marked by low, moderate, and high parental financial support. Low higher education experience, relatively high work experience, and low financial literacy are likely to be markers of at least one profile. For at least one profile that receives high parental financial support, college enrollment is expected to be higher and work experience is expected to be relatively low.

2. *Do emerging adults with different patterns of capital in emerging adulthood differ in their financial behaviors?*

The aim of the second research question is to understand how different configurations of family and human capital are associated with positive financial behaviors such as budgeting and saving. Previous research indicates that higher financial knowledge and youth work experience are related to healthy financial behaviors (de Bassa Scheresberg, 2013; Shim et al., 2010). Working more hours late in high school and during college may be a substitute for parental financial support that provides an emerging adult with more opportunities to practice financial behaviors since they handle their own financial affairs. Thus, groups of individuals with higher financial knowledge scores and at least some work experience will likely have higher positive financial behavior enactment.

Using a nationally representative sample, one study of 17 to 21 year olds found that study participants with high net worth parents felt less skilled at money management (Kim & Chatterjee, 2013). It could be the case that study participants with high net worth parents received high amounts of financial support from their parents, and therefore did not feel the needed to tightly manage their money. For the present study, configurations with relatively higher parental financial support are expected to enact positive financial behaviors at lower rates.

CHAPTER 3. METHODOLOGY

Sample

Data for this study were drawn from the Flourishing Families Project (FFP) – a longitudinal study carried out in the School of Family Life at Brigham Young University. The purpose of FFP is to examine the impact of family processes on the development of children from late childhood through adolescence and into emerging adulthood. In total, ten waves of data were collected annually from 2007 to 2016.

A total of 500 families from a large Northwestern city were selected to participate in the study during the first eight months of 2007. An initial 692 families with a child between the ages of 10 and 14 were contacted via the Polk Directoiries/InfoUSA national telephone survey database. Of these families, 423 agreed to participate. An additional 77 families were recruited through personal referrals, fliers, and other means in order to increase sample size and ensure socioeconomic and ethnic diversity. From waves 1 through 9, parents and the focal child participated in observational activities and responded to surveys. In wave 10, the focal child was the only participant surveyed; a total of 438 respondents were surveyed in wave 10.

Selection of Analytic Sample

For the purpose of this study, it was important that the analytic sample consist of individuals who were in a similar stage of life. This study examines college age, early emerging adults. The majority of the sample is composed of emerging adults who were only one to three years post high school at the time of wave 10 in 2016. However, there was a small subset of respondents who were still in high school at the time of wave 10 and another, larger subset who were four or more years post high school. Respondents still in high school would likely not yet have had the opportunity to enroll in higher education and were also more likely to have been fully financially supported by their parents. Therefore, this segment of the sample were still adolescents. Of those who were four or more years removed from high school at wave 10, some had already graduated from college and many reported receiving little to no financial support from their parents. Although it was not clear that all respondents who were four or more years removed from high school had entered their adult careers and some were still in college, three years removed from college was used as a cut point to distinguish those who were early emerging adults from those who may have transitioned into late emerging adulthood.

To be considered for sample selection, respondents needed to fulfill one of the following high school completion criteria between 2013 and 2015: graduated from high school, completed high school equivalency, or discontinued high school. A high school completion year between 2013 and 2015 guaranteed that the analytic sample consisted of emerging adults who would be at least one year removed from high school at the time of wave 10 in 2016 but would likely not yet have had enough time to complete a 4-year degree from a college or university.

After eliminating respondents that did not meet the selection criteria, the final analytic sample consisted of 333 emerging adults who were between the ages of 18 and 23 at the time of data collection for wave 10 ($M = 20.04, SD = 0.78$). Nearly 72% of the sample is racially White. Just over half of the sample is female. In terms of family socioeconomic status, the majority of respondents came from families that are highly educated; 73% of the sample had at least one parent with a bachelor's, graduate, or professional degree.

Additionally, over 30% of respondents' families had annual incomes above $100,000 across multiple waves. Descriptive statistics are displayed in Table 1.

Method

Latent profile analysis (LPA) is a type of mixture model that aims to categorize a heterogeneous sample into latent categorical classes that have similar response patterns on a set of continuous, manifest indicators (Nylund, Asparouhov, & Muthén, 2007). LPA is a type of latent class analysis. Collins and Lanza (2010) state that the purpose of latent class analysis is to discover a set of meaningful latent classes that best represent response patterns within the data and show the prevalence of each latent class. Latent class models can help make sense of complex patterns in data by estimating a parsimonious, probabilistic model.

LPA estimates a latent structure model with a single categorical variable using observed continuous indicators that are outcomes of the unobserved latent categorical variable (Vermunt & Magidson, 2002). In general, latent class and latent profile analysis assume local independence, which means that within each class, observed variables are only related to each other through the latent variable and do not have correlated error terms (Lanza and Collins, 2010). LPA also generally assumes equality of variance across classes so that configurations have the same form but different means and locations in the distributions of the indicator variables (Vermunt & Magidson, 2002).

Table 1

Descriptive statistics (N = 333)

	n (%)	*Mean (SD)*	*Range*
Demographic Characteristics			
Gender[a]			
Female	178(53.45)	–	–
Male	155(46.55)	–	–
Race/Ethnicity[b]			
White	239(71.77)	–	–
Multiethnic/Other	36(10.81)	–	–
Black	32(9.61)	–	–
Asian	16(4.80)	–	–
Hispanic	2(0.60)	–	–
High School Graduation Year[c]			
2013	116(34.83)	–	–
2014	147(44.14)	–	–
2015	70(21.02)	–	–
Family Characteristics			
Parent Education[d]			
Less than 4-year degree	89(26.73)	–	–
4-year degree	117(35.14)	–	–
Graduate or professional degree	127(38.14)	–	–
Family income[e]	–	$101,927($80,198)	$0 – $553,333
Emerging Adult Capital			
Financial knowledge[f]	–	1.70(0.93)	0 – 3
Parental financial support[g]	–	3.76(2.12)	0 – 7
Work hours[h]	–	13.61(9.48)	0 – 47
Years of college enrollment[i]	–	1.69(0.98)	0 –3
Dependent Variable			
Financial behavior[j]	–	2.98(1.03)	0 – 5

Note. Measures come from waves 1 – 10 of the Flourishing Families Project.
[a] Gender was reported by the primary caregiver in wave 1.
[b] Race/ethnicity was reported by the primary caregiver in wave1; race/ethnicity was missing for 6 cases.
[c] High school graduation year was determined from a combination of parent and child reports in waves 7, 8 and 9.
[d] Parent education was computed from the highest level of education reported from either member of the parental unit in wave 1.
[e] Family income was computed as the mean of couple reports of annual income in waves 1, 4, and 5; two families have missing values for family income.
[f] Financial knowledge was reported in wave 10.
[g] Parental financial support was reported in wave 10.
[h] Work hours were computed as the mean of weekly work hours across a four year period reported by respondents in waves 7 – 10.
[i] Years of college enrollment were calculated from respondent reports in waves 7 – 10.
[j] Financial behavior items were reported in wave 10.

Measures

Latent Profile Analysis Indicators

The manifest, continuous indicators for the LPA consist of financial knowledge, parental financial support, employment experience, and college enrollment.

Parental financial support. In FFP wave 10, respondents were asked "What proportion of your living expenses (food, housing, clothing, transportation, insurance, entertainment, and other money you spend) would you estimate is provided by your parents?" This item was written by FFP researchers. Responses were asked in seven categories: none (0%), very little (1% - 4%), some (5% - 24%), moderate (25% - 49%), majority (50% - 74%), and most (75% - 94%), almost all (95% - 99%), and all (100%). Responses range from 0 to 7; this measure is included in the LPA as a continuous variable.

Financial knowledge. Three financial knowledge questions were asked in FFP wave 10. Respondents were asked to pick the correct answer to the following questions which were adapted from a longer scale used in the Study on Collegiate Financial Wellness (2016):

1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? [Correct answer: More than $110];
2. Suppose you borrowed $5,000 to help cover college expenses for the coming year. You can choose to repay this loan over 10 years, 20 years, or 30 years. Which of these repayment options will cost you the least amount of money over the length of the repayment period? [Correct answer: 10 year repayment option]; and
3. All paycheck stubs show your gross pay (the total amount you earned before any taxes were taken out for the pay period) and the net pay (the amount of

your check after all taxes). The taxes that are taken out include Federal, state, and local income tax, Social Security tax, and Medicare tax. On average, what percentage of your income would you expect to receive as take-home pay? [Correct answer: 75-84%].

Items that were answered correctly were scored as 1, and incorrect responses were scored as 0. A financial knowledge score was created by summing together correct responses so that the possible range for this measure is 0 to 3. The majority of respondents answered at least one financial knowledge question correctly; 39.34% answered two questions correctly and 21.02% answered all three questions correctly. Only 11.41% of respondents answered none of the questions correctly.

Employment experience. During data collection in 2013, 2014, 2015, and 2016 (waves 7 – 10) emerging adults were asked “How many paid jobs do you currently have?” and “If you are working for pay now, how many hours per week do you work on average?” All responses were entered as open-ended answers. Based on these open-ended responses, a numerical variable was created to represent weekly hours worked during each year. The majority of respondents reported a single number of hours worked per week either listed in numerals or written out in letters. Some respondents reported a range of weekly hours worked. For these cases, the mean of the range was recorded as the number of hours worked per week. Other respondents reported only working during the summer. In these cases, it was assumed that the summer consisted of three moths which amounts to twelve weeks. The number of hours the respondent reported working during the summer was multiplied by twelve and divided by fifty-two in order to arrive at an estimate of weekly hours worked that could be compared to those who worked year-round. If a response did not actually include numerical information (e.g. "I work irregular hours" or "I start a new job next week") or otherwise could not be deciphered, the response was recorded as missing. A mean score across all four years of reported weekly work hours was calculated to serve as a continuous measure of work experience.

Higher education experience. During 2013, 2014, 2015, and 2016 (waves 7 – 10), emerging adults reported whether or not they had been enrolled in higher education during the previous 12-months. For the purposes of this study, a respondent is considered enrolled in college if they responded yes to being a student at a community college, a 4-year college/university, or a vocational training program. All affirmative responses across this four year period were added together to calculate years of college enrollment.

Dependent Variable: Financial Behavior

Financial management behavior consists of five items adapted from the Financial Management Behavior Scale (Dew & Xiao, 2011). In wave 10, respondents were asked how often they engaged in seven different financial activities in the past six months which included: (1) paid bills on time; (2) kept a written or electronic record of monthly expenses; (3) stayed within your budget or spending plan; (4) paid off credit card balance in full each month; (5) made only minimum payments on a loan; (6) began or maintained an emergency savings fund; and (7) saved money from every paycheck. The response categories ranged from 1 (never) to 5 (always) as well as a "does not apply" response option.

After examining the responses to each item, it was discovered that 12% - 69% of respondents answered each of the seven items with the "does not apply" option. For the items corresponding to paying bills on time, keeping a record of spending, staying within a budget, maintaining an emergency fund, and saving regularly, the "does not apply" responses were grouped together with the "never" responses (see Dew & Xiao, 2011). Because it could not be determined whether or not emerging adults who responded "does not apply" to paying off credit cards or making a minimum payment on a loan held any sort of credit at all, these items were removed from the financial behavior scale. The final financial behavior scale for this study consists of five items has a Cronbach's alpha of .727.

Covariates

Dummy variables corresponding to gender, race/ethnicity (White, Minority), year of high school completion (2013, 2014, 2015), and the parental unit's highest level of education (less than a 4-year college degree, 4-year college degree, graduate/professional degree) were included in the analysis examining the relationship between the latent profiles and financial behavior. A continuous measure of parents' combined income was calculated as the mean of couple combined income from all waves when it was asked as an open ended response which includes waves 1, 4, and 5. The natural log of mean parental income was also used as a control in the regression analysis. Table 2 displays correlations, means, and standard deviations between all study variables.

Analysis Plan

Analyses for this study were completed using Stata 15 and Mplus 8.1. Full information maximum likelihood was used in assessing latent profile models and any missingness on indicator variables was handled within the analysis models.

Latent Profile Analysis

Because existing theory does not provide clear guidance on how many groups are plausible, the first step conducted in this analysis was to indirectly determine the number of latent profiles by running the one- to seven-class solutions. Six different fit statistics and an index of model differentiation were then used to assess the relative fit of each model. Fit statistics considered included the scaled log likelihood (LL) value (corrected for full information maximum likelihood estimation), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC, Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), and the bootstrapped likelihood ratio test (BLRT) (Nylund, Asparouhov, and Muthén, 2007). It is desirable for the scaled LL value to be larger and information criteria (AIC, BIC, aBIC) to be smaller. LMR-LRT and BLRT compare a given model with a model that has one fewer profiles. A statistically significant value indicates that the more complex model provides a better fit. Entropy is a coefficient between 0 and 1 that provides information about profile distinctiveness; entropy values closer to 1 indicate greater distinction between profiles and an entropy value greater than 0.8 is desirable (Clark & Muthén, 2009; Ramaswamy et al, 1993).

In addition to model fit indices, it is also important to consider interpretability of any class solution under consideration (see Lanza & Collins, 2010). Parsimony and classification probabilities, often called posterior probabilities, are important to examine when choosing between different class solutions. In general, class solutions in which there is homogeneity within classes and clear separation between classes are desirable. Homogeneity within classes means that members of a particular class are likely to provide the same observed response pattern. Separation between classes means that a particular response pattern is characteristic of only one class. In addition to the entropy coefficient, posterior probabilities for individual cases and averaged across classes also provide information about how well the model provides separation between classes and homogeneity within classes. It is desirable for average posterior probabilities for each class to be close to 1 and for each case to have a large posterior probability close to 1 for only one of the classes extracted.

Before conducting latent profile analyses, indicator variables were standardized into z-scores for ease of interpretation. Following recommendations from Geiser (2013) for conducting latent class analyses in Mplus, latent class models were tested with different random start values over 2,000 to ensure that the best log likelihood value is replicated which suggests that the model accurately reflects patterns in the data. Additionally, an adequate number of initial stage iterations were used (50 – 100) as well as a tight convergence criterion (.0000001) in order to avoid local maxima.

After determining the preferable number of latent profiles that reflect heterogeneity between groups and homogeneity within groups, the make-up of each group was analyzed. The number of respondents in each group and means, standard deviations, standard errors, minimum, and maximum of each indicator within each group were evaluated. This information was used to assign a name to each group.

Relationship between Latent Profile Membership and Financial Behavior

The first step in examining the relationship between latent profile membership and financial behavior was to examine mean group differences. This was accomplished by using the BCH procedure in Mplus which produces Wald chi-square tests to analyze differences between profile means on outcome variables. The overall financial behavior scale and the five individual items that make up the scale were evaluated. The advantage of using the BCH procedure in Mplus is that it accounts for uncertainty in class membership by assigning weights that account for measurement error of the latent class variable (Asparouhov & Muthén, 2014).

Finally, ordinary least squares regression analysis was carried out in Stata to understand the association between latent profile membership and positive financial behaviors with the inclusion of individual and parent control variables. Respondents were assigned to their most likely profile membership using posterior probabilities. While assigning individuals based on most likely class membership may lead to underestimating standard errors and thus biased estimates, Clark and Muthén (2009) state that most likely class membership may be acceptable if a latent class model has entropy of 0.8 or greater. A higher entropy value indicates adequate class separation. However, Clark and Muthén do caution that a more stringent criterion for deciding statistical significance than $p<.05$ should be used.

Table 2

Study Variable Correlations, Means, and Standard Deviations (N = 333)

Variables	1	2	3	4	5	6	7	8	9	10
1. Financial Knowledge	–									
2. Parental Financial Support	.125*	–								
3. Work Hours	.003	-.316***	–							
4. Years Enrolled in College	.165**	.130*	-.050	–						
5. Financial Behavior	.145**	-.288***	.201***	-.005	_					
6. Male	.198***	.083	-.001	-.013	.063	_				
7. Racial/Ethnic Minority	-.102	-.013	-.035	-.125*	-.105	-.016	_			
8. Year of High School Completion	.005	.137*	-.122*	-.468***	-.022	-.062	- .011	_		
9. Parental Education Level	.124*	.322***	-.149**	.282***	-.092	.093	.226***	.032	_	
10. Family income	.022	.242***	-.167**	.144**	-.151**	.021	-.144*	.062	.408***	_
M	1.700	3.754	13.610	1.685	2.982	_	_	_	_	$101,927
SD	0.928	2.120	9.478	0.975	1.035	_	_	_	_	$80,197

Note. Racial/Ethnic Minority if a dichotomous variable equal to one if a racial/ethnic minority and 0 otherwise. Year of High School Completion is a categorical variable corresponding to completing high school in 2013, 2014, or 2015. Parent education level is categorical and corresponds to less than a 4-year college degree, a 4-year college degree, or a graduate/professional school degree.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

CHAPTER 4. RESULTS

Latent Profile Analysis

Selection of the latent profile model was carried out by comparing the one- through six-class solutions. A seven-class model was run, but the best log likelihood value could not be replicated, which suggests that seven-class solution does not reflect the nature of patterns in the data (see Geiser, 2013). Fit statistics for the one- through six-class models are shown in Table 3. Moving from the three-class model to the four-class model provides significant improvements to model fit. For the four-class solution, BIC and sample-size adjusted BIC have the lowest values of any model and significant Lo-Mendell-Rubin likelihood ratio and bootstrapped likelihood ratio tests indicate a better fit than the three-class solution. The Lo-Mendell-Rubin likelihood ratio and bootstrapped likelihood ratio tests for the five-class solution are not significant suggesting that the five-class solution is not a better fit than the four-class solution. Nylund, Asparouhov, and Muthén's (2007) guidelines for LCA model selection recommend choosing the model with the lowest BIC value and the (k-1)-solution after the first non-significant BLRT value has been reached for the k-class solution. Thus, even though the six-class model had a significant BLRT value, the four-class model was selected as the optimal solution.

Not only do the fit indices suggest that the four-class model is the best fit, but four latent profiles also yield the most parsimonious model with the highest entropy coefficient (.92). The average posterior probabilities for most likely class membership of the four different classes ranged from 0.957 to 0.994. The lowest posterior probability for the most likely class membership across all cases was .723 with the majority of cases having posterior probabilities for most likely class membership above .900. Taken together, these results suggest high class separation and homogeneity within classes.

Table 3

Fit statistics and entropy for full-sample LPA models with 1 – 6 profiles

No. of profiles	LL	AIC	BIC	sBIC	LMR-LRT	BLRT	Entropy	N for each profile
1	0.825	3792.046	3822.511	3797.135	-	-	-	P1 = 333
2	0.924	3702.490	3751.996	3710.759	96.242 p=.000	99.556 p=.000	.826	P1 = 233 P2 = 100
3	0.965	3680.955	3749.502	3692.405	30.485 p=.004	31.535 p=.000	.707	P1 = 140 P2 = 97 P3 = 96
4	0.932	3641.228	3728.815	3655.858	48.072 p=.000	49.727 p=.000	.920	P1 = 139 P2 = 69 P3 = 63 P4 = 62
5	0.916	3642.912	3749.540	3660.723	8.039 p=.277	8.315 p=.650	.889	P1 = 139 P2 = 69 P3 = 62 P4 = 36 P5 = 27
6	1.013	3637.411	3763.080	3658.401	18.148 p=.147	18.773 p=.000	.851	P1 = 111 P2 = 68 P3 = 62 P4 = 35 P5 = 29 P6 = 28

Note. LL scaled loglikelihood (corrected for FIML), *AIC* Akaike Information Criterion, *BIC* Bayesian Information Criterion, *aBIC* sample-size adjusted Bayesian Information Criterion, *LMR-LRT* Lo-Mendell-Rubin likelihood ratio test, *BLRT* bootstrapped likelihood ratio test.

Table 4 reports mean levels of parental financial support, financial knowledge, work experience, and years of higher education for the four-profile solution and Figure 3 provides a visual depiction of the capital configurations using standardized means (z-scores). Overall, each of the four profiles are defined by the amount of parental financial support they receive.

Profile 1 represents a group of emerging adults who receive a moderately high amount of parental financial support. Respondents in *Moderate High Support* profile indicated that 50 – 94% of their expenses were paid by their parents. This group consisted of emerging adults who had a moderate amount of work experience, and 88% of members of the *Moderate High Support* profile were enrolled in higher education for at least one year. This profile represents 42% of the full sample (n = 139).

Profile 2 consists of emerging adults that received all or close to all of their financial support from their parents. All emerging adults in the *High Support* profile reported that their parents funded 95 – 100% of their total expenses. Members of the *High Support* profile had the lowest mean work experience of any of the four groups. Similar to the *Moderate High Support* profile, 87% of members in the *High Support* group had been enrolled in higher education for at least one year. Close to 21% of the full sample belong to the Highly Supported profile (n = 69).

Profile 3 represents 19% of the sample (n = 63) and is representative of emerging adults with little to no parental financial support and relatively higher work experience. Members of the *Low Support* group reported that no more than 4% of their total expenses were paid by their parents. As a group, the *Low Support* profile had the most work experience and had the fewest number of individuals with any higher education enrollment (67% reported enrollment in higher education at least once).

Finally, Profile 4 was composed of emerging adults who reported 5 – 49% of their total financial support coming from their parents. This *Moderate Low Support* profile constitutes just over 18% of the full sample (n = 62). The *Moderate Low Support* profile as a group had mean work experience just slightly above the full sample mean. This group had the highest exposure to higher education with 92% of group members reporting enrollment at least once.

Table 4

Capital indicator means for the 4-profile model

Capital Profiles		Capital Indicators			
		Parental Financial Support	Financial Knowledge	Work Experience	Higher Education
		M (SE)	*M* (SE)	*M* (SE)	*M* (SE)
Moderate High Support	(*n* = 139)	**4.57 (0.04)**	1.80 (0.08)	13.85 (0.79)	**1.86 (0.08)**
High Support	(*n* = 69)	**6.39 (0.06)**	1.74 (0.12)	**7.72 (0.89)**	1.57 (0.11)
Low Support	(*n* = 63)	**0.33 (0.06)**	1.52 (0.10)	**17.71 (1.30)**	**1.22 (0.13)**
Moderate Low Support	(*n* = 62)	**2.47 (0.06)**	1.60 (0.12)	15.45 (1.01)	**1.88 (0.11)**
Full Sample	(*n* = 333)	3.75 (0.12)	1.70 (0.05)	13.60 (0.52)	1.68 (0.05)

Note. Bolded values indicate the profile mean is significantly different than the full sample mean at p<.05.
N = 333.

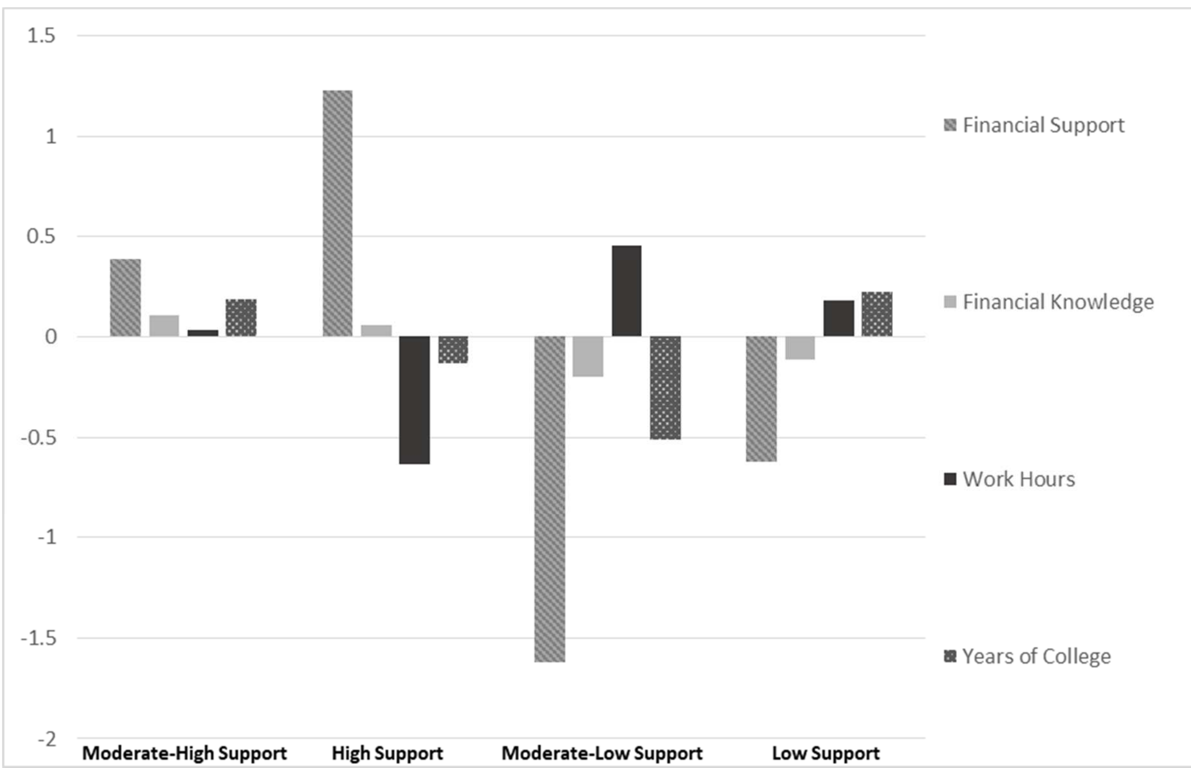

Figure 2. Characteristics of the latent profiles on the indicator variables. Means of capital indicators are z-scores.

No single profile had significantly higher or lower financial knowledge scores. The distribution of financial knowledge scores within the four different profiles was similar to the full sample distribution of financial knowledge scores. Likewise, the means of financial knowledge for each group do not significantly differ from the mean for the full sample.

Relationship between Profile Membership and Financial Behaviors

Wald chi-square tests were conducted to evaluate mean differences between latent profiles on the financial behavior scale and on individual items within the scale. This was followed by a hierarchical OLS regression analysis to evaluate the association between latent profile membership and the financial behaviors scale controlling for individual and family covariates.

Profile Mean Differences on Financial Behaviors

The results of the Wald chi-square tests are shown in Table 5. The *High Support* profile exhibited the lowest mean value on the financial behavior scale and it was significantly different from the mean values of the other three profiles. The *High Support* profile also displayed the lowest mean values across all financial behavior items. The *Low Support* group had the highest mean scores across all items except for save regularly. Overall, regular implementation of positive financial behaviors are moderate to low on average among all profiles except for paying bills on time for the *Low Support* profile with a mean of 4.27. Tracking spending and saving in an emergency fund were the least practiced financial behaviors across all groups.

Table 5

Differences in financial behavior scale and items as a function of profile membership

Capital Profiles		Individual Financial Behaviors					
		Financial Behavior Scale	Pay Bills on Time	Budget	Track Spending	Save Regularly	Emergency Fund
		M (SE)	*M (SE)*	*M (SE)*	*M (SE)*	*M (SE)*	*M (SE)*
Moderate High Support	(*n* = 139)	3.11 (0.08)[a]	3.64 (0.15)[a,b]	3.23 (0.11)[a]	2.69 (0.13)[a,b]	3.57 (0.12)[a]	2.45 (0.14)[a]
High Support	(*n* = 69)	2.29 (0.13)[a,b,c]	2.33 (0.22)[a,c,d]	2.53 (0.18)[a,b,c]	2.19 (0.20)[a,c]	2.74 (0.19)[a,b]	1.65 (0.14)[a,b,c]
Low Support	(*n* = 63)	3.31 (0.12)[b]	4.27 (0.14)[b,c]	3.51 (0.15)[b]	3.20 (0.20)[b,c,d]	3.16 (0.18)	2.52 (0.20)[b]
Moderate Low Support	(*n* = 62)	3.12 (0.12)[c]	3.84 (0.18)[d]	3.07 (0.16)[c]	2.64 (0.18)[d]	3.30 (0.17)[b]	2.70 (0.20)[c]
Full Sample	(*n* = 333)	2.98 (0.06)	3.52(0.09)	3.11(0.07)	2.67(0.08)	3.27(0.08)	2.34(0.08)

Note. Matching letters in the same column indicate means are significantly different at p<.05 based on Wald chi-square tests.

Regression Analysis

OLS regression was carried out in Stata. Emerging adults were assigned to their maximum probability assignment profile based on their posterior probabilities. Table 6 presents the results for three different model specifications: (1) latent profiles as the only independent variable and the *Moderate High Support* profile serving as the reference; (2) the addition of individual-level control variables including gender, race/ethnicity, and year of high school completion; and (3) the addition of parent level control variables including parent education and the natural logarithm of parent combined income.

In the first model specification, only the *High Support* profile has a statistically significant coefficient ($p<.001$). After adding individual characteristics to the model, the *Low Support* profile becomes statistically significant at $p<.05$. However, following Clark and Muthén's (2009) criteria of using a more stringent cutoff point to determine statistical significance when using maximum probability assignment, this estimate may be biased. After adding parent-level control variables, the intercept of financial behavior is statistically significant ($B=3.88$, $p<.001$), the coefficient for the *Low Support* profile is no longer significant at any level, and the coefficient for the *High Support* profile remains significant ($B = -.795$, $p<.001$). Holding all other variables constant, a member of the *High Support* profile is estimated to have a financial behavior score of 3.09. Interestingly, the coefficient for race/ethnicity becomes significant in the final model specification indicating that, after controlling for parental education and family income, minority emerging adults are slightly less likely to practice positive financial behaviors compared to White emerging adults. The final model specification explains 15.2% of the variation in financial behavior.

Table 6

Hierarchical linear regression of latent profiles' association with financial behavior

Predictor Variables	*Model 1*		*Model 2*		*Model 3*	
	B	*SE*	B	*SE*	B	*SE*
Latent Profile (Reference: Moderate high)						
Low support	.263	.151	.301*	.151	.240	.160
Moderate low support	-.016	.149	-.008	.149	-.028	.151
High support	-.823***	.145	-.819***	.146	-.795***	.148
Individual Characteristics						
Gender (reference: Male)			.186	.108	.193	.109
Race/Ethnicity (reference: White)			-.225	.122	-.273*	.129
High completion 2013 (reference: 2014)			-.110	.122	-.113	.123
High completion 2015 (reference: 2014)			-.065	.146	-.058	.146
Parent Characteristics						
Less than 4-year degree (reference: graduate)					.082	.164
4-year degree (reference: graduate)					.014	.129
Parent income (log)					-.067	.085
Constant	3.120***	.083	3.135***	.120	3.880***	1.006
R^2	.127		.148		.152	
Change in R^2	.127		.021		.004	

*$p < .05$. **$p < .01$. ***$p < .001$.

CHAPTER 5. DISCUSSION AND CONCLUSION

This study aimed to examine different pathways of economic and financial flourishing and floundering among a sample of emerging adults using a person-centered research approach. Parental financial support, financial knowledge, work experience, and higher education experience were conceptualized as forms of capital. Different patterns of capital were expected to be related to positive financial behaviors such that some emerging adults would enact financial behaviors that would help them flourish and other emerging adults would flounder in their uptake of healthy financial behaviors.

Discussion of Findings

Latent profile analyses yielded a four-class solution as the best fitting model. Each of these four classes – *Moderate High Support*, *High Support*, *Low Support*, and *Moderate Low Support* – were rigidly characterized by specific levels of parental financial support. All members of the *Low Support* profile had responses of 0 or 1 (0% or 1 – 4% of support, respectively) on the parental financial support measure, all members of the *Moderate Low Support* profile had responses of 2 or 3 (5 – 24% or 25 – 49%), all members of the *Moderate High Support* profile had responses of 4 or 5 (50 – 74% or 75 – 94%), and all members of the *High Support* profile had responses of 6 or 7 (95 – 99% or 100%). For the work experience and higher education enrollment indicators, group mean differences were found for multiple groups. However, for the financial knowledge indicator, none of the four groups had means that were statistically different from the mean of the full sample.

The *Low Support* profile as a group exhibited the highest mean work experience at about 18 hours per week for four years and the lowest mean higher education experience. This group had the highest mean financial behavior score. As a group, they reported paying bills on time at a significantly higher rate than the *Moderate High Support* and *High Support* profiles (*M = 4.27*, *SE = 0.14)* and they had a higher mean than any other group for tracking spending (*M = 3.20, SE = 0.20)*. It could be the case that because many members of the *Low Support* have very little to no parental financial support, they exhibit more financial responsibility as demonstrated by paying bills on time. Some individuals in this group may be tracking their spending out of necessity because of very tight finances, rather than as a good financial habit. One study examined tracking spending and staying within a budget as financial coping behaviors within a sample of emerging adult college students and found evidence that emerging adult who engaged in these behaviors experienced higher amounts of financial stress (Serido, Shim, Mishra, & Tang, 2010). Further research is needed to understand how levels of emerging adult capital like parental financial support, specific financial behaviors, and financial stress may be related.

As a group, the *Moderate Low Support* profile had mean work experience equivalent to 15 hours per week for four years and the largest mean enrollment in higher education. The *Moderate High Support* profile, as a group, displayed a mean of almost 14 hours of work per week for four years and had a mean enrollment in higher education very similar to that of the *Moderate Low Support* profile. Both of these profiles displayed similar mean scores that were not statistically significantly different from each other on the financial behavior scale and five financial behavior items. As groups, the *Moderate Low* and *Moderate High* profiles' scores on these items suggest intermittent to somewhat frequent practice of positive financial behaviors.

Finally, the *High Support* profile had mean work experience of almost 8 hours per week for four years. As a group, the *High Support* profile had higher mean higher education experience than the *Low Support* profile but lower than either of the *Moderate* profiles. The *High Support* profile had the lowest mean scores across all financial behavior items, which were significantly different from at least two of the other capital profiles. Regression analyses showed that membership in the *High Support* profile is associated with a lower overall financial behavior compared to membership in the *Moderate High Support* profile, even after controlling for individual and parent characteristics. These findings suggest that members of the *High Support* profile may be missing out on opportunities for experiential learning and positive habit formation in their financial behaviors. A longitudinal study of emerging adults found that financial behaviors practiced by emerging adults during college were associated with financial well-being later in emerging adulthood (Burcher, Serido, Danes, Rudi, & Shim, 2018). Thus, understanding how dependency and responsibility operate in families that provide very high financial support to emerging adult children is an important line of research to follow. How dependency and responsibility take shape in families that provide high amounts of financial support may have implications for economic and financial well-being for those emerging adults.

Limitations

The current study is exploratory in nature. Patterns detected by latent profile analysis may be sample specific and would need to be replicated in representative samples of emerging adults to be considered generalizable. The majority of families that took part in the Flourishing Families Project were racially White, had highly educated parents, and were upper-middle to high income. Thus, studying the ways that family and individual capital are associated with financial behavior and other types of financial outcomes with more diverse emerging adult samples are needed.

Additionally, care should be taken when discussing subgroups detected by latent class analysis versus the individuals assigned to those subgroups. Sterba and Bauer (2010) discuss latent profile analysis and other types of probabilistic classification models as techniques that provide information about the average experience of the group. However, there are still individual characteristics and experiences that groupings may obscure.

This study only examined variations in financial behavior by profiles of family and human capital. Variables such as financial stress, financial pressure, financial satisfaction, accumulated debt, and financial self-efficacy are other possibilities for understanding ways that subgroups of emerging adults are flourishing or floundering.

Conclusion

The current study found that separation between profiles in emerging adult capital were largely driven by differences in parental financial support. This finding has interesting implications for future research and the financial education and parenting of emerging adults in order to help them flourish rather than flounder. The *Low Support* group practiced some of the positive financial behaviors most frequently while the High Support profile practiced all of the positive financial behaviors the least frequently. Even though the *Low Support* profile as group practiced some financial behaviors, such as tracking spending more frequently than other groups, some of their financial behaviors were practiced at the same mean frequency as groups that had moderate parental financial support. Thus, the *Low Support* group may not be flourishing in the financial behavioral practices. Rather, they may be tightly controlling their spending due to lack of funding or financial stress. Additional research is needed to understand why certain financial behaviors are potentially enacted at greater frequencies in some groups of emerging adults and not in others.

The *High Support* group's lower enactment of all positive financial behaviors suggests high dependency on parents not just for financial support, but quite possibly for everyday financial decision-making as well. Financial independence is one of the ways emerging adults identify attainment of adulthood (Arnett, 2006, 2014), so remaining fully financially dependent on parents into the late teens and early twenties likely has implications for self-efficacy and psychological well-being. Many emerging adults desire opportunities to engage in experiential learning but rely on parents to provide those opportunities (LeBaron, Hill, Rosa, & Marks, 2018). Among personal finance educators at colleges, universities, and other organizations that serve emerging adults, thought should be given to how to educate highly supported emerging adults who may never or rarely engage in positive financial behaviors because parents may control the purse strings and possibly financial decision making.

While this study found that parental financial support differentiated groups of emerging adults, future research should examine if other forms of capital shape economic and financial flourishing and floundering among emerging adults. Some possibilities include more comprehensive measure of financial literacy, understanding of numeracy, own earnings, financial aid availability, and social and financial support available at colleges, universities, or other institutions that serve emerging adults.

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APPENDIX A. IRB EXEMPT STATUS

IOWA STATE UNIVERSITY
OF SCIENCE AND TECHNOLOGY

Institutional Review Board
Office for Responsible Research
Vice President for Research
2420 Lincoln Way, Suite 202
Ames, Iowa 50014
515 294-4566

Date:	04/01/2019		
To:	Sara Ray	Clinton G Gudmunson	
From:	Office for Responsible Research		
Title:	**Economic Flourishing and Floundering in Emerging Adulthood**		
IRB ID:	**19-148**		
Submission Type:	Initial Submission	**Determination Date:**	04/01/2019

The project referenced above has been reviewed and the following determination has been made. The project:

Is research that does not involve human subjects according to federal regulations.

Accordingly, this project does not need IRB approval and you may proceed at any time. We do, however, urge you to protect the rights of your participants in the same ways you would if IRB approval were required. For example, best practices include informing participants that involvement in the project is voluntary and maintaining confidentiality as appropriate. Additionally, approval from other entities may be needed depending on your project. This IRB determination in no way implies or guarantees that permission from these other entities will be granted.

If you modify the project, we recommend communicating with the IRB staff to ensure that the modifications do not change this determination such that IRB approval is required.

Please don't hesitate to contact us if you have questions or concerns at 515-294-4566 or IRB@iastate.edu.

IRB 03/2018

APPENDIX B. MPLUS OUTPUT FOR 4-PROFILE SOLUTION

```
Mplus VERSION 8.1
MUTHEN & MUTHEN
04/13/2019   7:37 PM

INPUT INSTRUCTIONS

  TITLE: Thesis LPA Model 4-Class optseed no covariates

  DATA:
    FILE is T_FFP_Mplus_333.dat;

  VARIABLE:
    Names are
       male finlit minority phedu1 phedu2 phedu3 wrkhrs
       finsup hs2013 hs2014 hs2015 pcombinc paybills track
       budget emerfund save finbeh hedu zfinsup zfinlit zwrkhrs
       zhedu ID;
    MISSING ARE ALL (-9999);
    USEVARIABLES = zFinSup zFinLit zWrkHrs zHEDU;
    CLASSES = class(4);
    IDVARIABLE = ID;

  ANALYSIS:
    TYPE = MIXTURE;
    STARTS = 0;
    OPTSEED = 789528;
      LRTBOOTSTRAP = 100 50 100 50;


  MODEL:
    %OVERALL%

  OUTPUT: Tech11 Tech14;

  SAVEDATA:
    format is free;



*** WARNING in MODEL command
  All variables are uncorrelated with all other variables within class.
  Check that this is what is intended.
   1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS



Thesis LPA Model 4-Class optseed no covariates

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                         333

Number of dependent variables                                    4
Number of independent variables                                  0
Number of continuous latent variables                            0
Number of categorical latent variables                           1

Observed dependent variables

  Continuous
   ZFINSUP     ZFINLIT     ZWRKHRS     ZHEDU

Categorical latent variables
```

Page: 1

```
   CLASS

Variables with special functions

  ID variable          ID

Estimator                                                    MLR
Information matrix                                      OBSERVED
Optimization Specifications for the Quasi-Newton Algorithm for
Continuous Outcomes
  Maximum number of iterations                               100
  Convergence criterion                                0.100D-05
Optimization Specifications for the EM Algorithm
  Maximum number of iterations                               500
  Convergence criteria
    Loglikelihood change                               0.100D-06
    Relative loglikelihood change                      0.100D-06
    Derivative                                         0.100D-05
Optimization Specifications for the M step of the EM Algorithm for
Categorical Latent variables
  Number of M step iterations                                  1
  M step convergence criterion                         0.100D-05
  Basis for M step termination                         ITERATION
Optimization Specifications for the M step of the EM Algorithm for
Censored, Binary or Ordered Categorical (Ordinal), Unordered
Categorical (Nominal) and Count Outcomes
  Number of M step iterations                                  1
  M step convergence criterion                         0.100D-05
  Basis for M step termination                         ITERATION
  Maximum value for logit thresholds                          15
  Minimum value for logit thresholds                         -15
  Minimum expected cell size for chi-square            0.100D-01
Maximum number of iterations for H1                         2000
Convergence criterion for H1                           0.100D-03
Optimization algorithm                                       EMA
Random Starts Specifications
  Random seed for analysis                                789528

Input data file(s)
  T FFP Mplus 333.dat
Input data format  FREE


SUMMARY OF DATA

     Number of missing data patterns             1
     Number of y missing data patterns           1
     Number of u missing data patterns           0


COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value   0.100


     PROPORTION OF DATA PRESENT FOR Y


           Covariance Coverage
              ZFINSUP       ZFINLIT       ZWRKHRS       ZHEDU
              ________      ________      ________      ________
 ZFINSUP        1.000
 ZFINLIT        1.000         1.000
 ZWRKHRS        1.000         1.000         1.000
```

```
ZHEDU          1.000        1.000        1.000        1.000


UNIVARIATE SAMPLE STATISTICS

     UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS

         Variable/         Mean/     Skewness/   Minimum/ % with                Percentile
s
        Sample Size      Variance    Kurtosis    Maximum  Min/Max      20%/60%    40%/80%
   Median

     ZFINSUP               0.000      -0.411      -1.771   12.61%      -0.827      0.116
    0.116
             333.000       0.997      -0.886       1.531    8.11%       0.588      1.060
     ZFINLIT               0.000      -0.232      -1.831   11.41%      -0.754      0.324
    0.324
             333.000       0.997      -0.798       1.401   21.02%       0.324      1.401
     ZWRKHRS               0.000       0.457      -1.436   11.41%      -0.908     -0.381
   -0.117
             333.000       0.997      -0.254       3.497    0.30%       0.173      0.806
     ZHEDU                 0.000      -0.331      -1.727   15.32%      -0.702      0.323
    0.323
             333.000       0.997      -0.861       1.348   21.32%       0.323      1.348

THE MODEL ESTIMATION TERMINATED NORMALLY


MODEL FIT INFORMATION

Number of Free Parameters                       23

Loglikelihood

          H0 Value                       -1797.614
          H0 Scaling Correction Factor      0.9315
            for MLR

Information Criteria

          Akaike (AIC)                    3641.228
          Bayesian (BIC)                  3728.815
          Sample-Size Adjusted BIC        3655.858
            (n* = (n + 2) / 24)


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THE ESTIMATED MODEL

    Latent
   Classes

       1         61.39766          0.18438
       2         68.75870          0.20648
       3        140.10754          0.42074
       4         62.73610          0.18840

FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
```

BASED ON ESTIMATED POSTERIOR PROBABILITIES

Latent Classes		
1	61.39766	0.18438
2	68.75870	0.20648
3	140.10754	0.42074
4	62.73610	0.18840

FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THEIR MOST LIKELY LATENT CLASS MEMBERSHIP

Class Counts and Proportions

Latent Classes		
1	63	0.18919
2	69	0.20721
3	139	0.41742
4	62	0.18619

CLASSIFICATION QUALITY

Entropy 0.920

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row)
by Latent Class (Column)

	1	2	3	4
1	0.969	0.000	0.000	0.031
2	0.000	0.962	0.038	0.000
3	0.000	0.017	0.978	0.005
4	0.006	0.000	0.026	0.968

Classification Probabilities for the Most Likely Latent Class Membership (Column)
by Latent Class (Row)

	1	2	3	4
1	0.994	0.000	0.000	0.006
2	0.000	0.966	0.034	0.000
3	0.000	0.019	0.970	0.011
4	0.032	0.000	0.012	0.957

Logits for the Classification Probabilities for the Most Likely Latent Class Membership (C
olumn)
by Latent Class (Row)

	1	2	3	4
1	5.074	-8.735	-8.735	0.000
2	0.000	13.781	10.440	0.000
3	-9.337	0.489	4.449	0.000
4	-3.410	-13.771	-4.419	0.000

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Latent Class 1				
Means				
ZFINSUP	-1.619	0.031	-52.814	0.000
ZFINLIT	-0.200	0.114	-1.749	0.080
ZWRKHRS	0.455	0.143	3.191	0.001
ZHEDU	-0.510	0.143	-3.573	0.000
Variances				
ZFINSUP	0.066	0.004	18.408	0.000
ZFINLIT	0.982	0.060	16.470	0.000
ZWRKHRS	0.869	0.069	12.593	0.000
ZHEDU	0.921	0.058	15.841	0.000
Latent Class 2				
Means				
ZFINSUP	1.229	0.037	33.610	0.000
ZFINLIT	0.059	0.134	0.439	0.661
ZWRKHRS	-0.635	0.096	-6.643	0.000
ZHEDU	-0.129	0.115	-1.126	0.260
Variances				
ZFINSUP	0.066	0.004	18.408	0.000
ZFINLIT	0.982	0.060	16.470	0.000
ZWRKHRS	0.869	0.069	12.593	0.000
ZHEDU	0.921	0.058	15.841	0.000
Latent Class 3				
Means				
ZFINSUP	0.386	0.026	15.002	0.000
ZFINLIT	0.109	0.088	1.238	0.216
ZWRKHRS	0.032	0.085	0.372	0.710
ZHEDU	0.186	0.084	2.214	0.027
Variances				
ZFINSUP	0.066	0.004	18.408	0.000
ZFINLIT	0.982	0.060	16.470	0.000
ZWRKHRS	0.869	0.069	12.593	0.000
ZHEDU	0.921	0.058	15.841	0.000
Latent Class 4				
Means				
ZFINSUP	-0.625	0.045	-13.968	0.000
ZFINLIT	-0.112	0.130	-0.857	0.392
ZWRKHRS	0.179	0.110	1.629	0.103
ZHEDU	0.225	0.119	1.894	0.058
Variances				
ZFINSUP	0.066	0.004	18.408	0.000
ZFINLIT	0.982	0.060	16.470	0.000
ZWRKHRS	0.869	0.069	12.593	0.000
ZHEDU	0.921	0.058	15.841	0.000

Categorical Latent Variables

Means

```
    CLASS#1            -0.022       0.192      -0.112       0.910
    CLASS#2             0.092       0.184       0.499       0.618
    CLASS#3             0.803       0.160       5.033       0.000


QUALITY OF NUMERICAL RESULTS

     Condition Number for the Information Matrix              0.855E-03
       (ratio of smallest to largest eigenvalue)


TECHNICAL 11 OUTPUT

     Random Starts Specifications for the k-1 Class Analysis Model
        Number of initial stage random starts                  20
        Number of final stage optimizations                     4



     VUONG-LO-MENDELL-RUBIN LIKELIHOOD RATIO TEST FOR 3 (H0) VERSUS 4 CLASSES

          H0 Loglikelihood Value                        -1822.478
          2 Times the Loglikelihood Difference             49.727
          Difference in the Number of Parameters                5
          Mean                                              3.057
          Standard Deviation                                6.141
          P-Value                                          0.0000

     LO-MENDELL-RUBIN ADJUSTED LRT TEST

          Value                                            48.072
          P-Value                                          0.0000


TECHNICAL 14 OUTPUT

     Random Starts Specifications for the k-1 Class Analysis Model
        Number of initial stage random starts                  20
        Number of final stage optimizations                     4

     Random Starts Specification for the k-1 Class Model for Generated Data
        Number of initial stage random starts                   0
        Number of final stage optimizations for the
           initial stage random starts                          0
     Random Starts Specification for the k Class Model for Generated Data
        Number of initial stage random starts                  40
        Number of final stage optimizations                     8
     Number of bootstrap draws requested                      100


     PARAMETRIC BOOTSTRAPPED LIKELIHOOD RATIO TEST FOR 3 (H0) VERSUS 4 CLASSES

          H0 Loglikelihood Value                        -1822.478
          2 Times the Loglikelihood Difference             49.727
          Difference in the Number of Parameters                5
          Approximate P-Value                              0.0000
          Successful Bootstrap Draws                          100


DIAGRAM INFORMATION

  Mplus diagrams are currently not available for Mixture analysis.
  No diagram output was produced.
```

APPENDIX C. MPLUS OUTPUT FOR FINANCIAL BEHAVIOR BY PROFILE

```
Mplus VERSION 8.1
MUTHEN & MUTHEN
04/15/2019   7:44 PM

INPUT INSTRUCTIONS

  TITLE: Thesis LPA Model 4-Class no optseed no covariates

  DATA:
    FILE is T_FFP_Mplus_333_Final.dat;

  VARIABLE:
    Names ARE zfinsup zfinlit zwrkhrs zhedu male finlit minority
      phedu1 phedu2 phedu3 wrkhrs   finsup hs2013 hs2014 hs2015 pcombinc
      paybills track budget emerfund save   finbeh hedu sixpp1 sixpp2
      sixpp3    sixpp4 sixpp5 sixpp6 profile6 ID;
    MISSING ARE ALL (-9999);
    USEVARIABLES = zFinSup zFinLit zWrkHrs zHEDU;
    CLASSES = class(4);
    IDVARIABLE = ID;
      AUXILIARY = (BCH) finbeh;

  ANALYSIS:
    TYPE = MIXTURE;
    STARTS = 0;
    OPTSEED = 789528;


  MODEL:
    %OVERALL%

  SAVEDATA:
    format is free;



*** WARNING in MODEL command
  All variables are uncorrelated with all other variables within class.
  Check that this is what is intended.
   1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS



Thesis LPA Model 4-Class no optseed no covariates

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                         333

Number of dependent variables                                    4
Number of independent variables                                  0
Number of continuous latent variables                            0
Number of categorical latent variables                           1

Observed dependent variables

  Continuous
   ZFINSUP     ZFINLIT     ZWRKHRS     ZHEDU

Observed auxiliary variables
   FINBEH

Categorical latent variables
```

Page: 1

```
   CLASS

Variables with special functions

  ID variable           ID

Estimator                                                    MLR
Information matrix                                      OBSERVED
Optimization Specifications for the Quasi-Newton Algorithm for
Continuous Outcomes
  Maximum number of iterations                               100
  Convergence criterion                                0.100D-05
Optimization Specifications for the EM Algorithm
  Maximum number of iterations                               500
  Convergence criteria
    Loglikelihood change                               0.100D-06
    Relative loglikelihood change                      0.100D-06
    Derivative                                         0.100D-05
Optimization Specifications for the M step of the EM Algorithm for
Categorical Latent variables
  Number of M step iterations                                  1
  M step convergence criterion                         0.100D-05
  Basis for M step termination                         ITERATION
Optimization Specifications for the M step of the EM Algorithm for
Censored, Binary or Ordered Categorical (Ordinal), Unordered
Categorical (Nominal) and Count Outcomes
  Number of M step iterations                                  1
  M step convergence criterion                         0.100D-05
  Basis for M step termination                         ITERATION
  Maximum value for logit thresholds                          15
  Minimum value for logit thresholds                         -15
  Minimum expected cell size for chi-square            0.100D-01
Maximum number of iterations for H1                         2000
Convergence criterion for H1                           0.100D-03
Optimization algorithm                                       EMA
Random Starts Specifications
  Random seed for analysis                                789528

Input data file(s)
  T FFP Mplus 333 Final.dat
Input data format  FREE


SUMMARY OF DATA

     Number of missing data patterns             1
     Number of y missing data patterns           1
     Number of u missing data patterns           0


COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value   0.100


     PROPORTION OF DATA PRESENT FOR Y


           Covariance Coverage
              ZFINSUP       ZFINLIT       ZWRKHRS       ZHEDU
              ________      ________      ________      ________
 ZFINSUP        1.000
 ZFINLIT        1.000         1.000
 ZWRKHRS        1.000         1.000         1.000
```

```
 ZHEDU          1.000         1.000         1.000         1.000


UNIVARIATE SAMPLE STATISTICS


     UNIVARIATE HIGHER-ORDER MOMENT DESCRIPTIVE STATISTICS

         Variable/         Mean/     Skewness/   Minimum/ % with                Percentile
s
        Sample Size      Variance    Kurtosis    Maximum  Min/Max      20%/60%    40%/80%
   Median

     ZFINSUP               0.000      -0.411      -1.771   12.61%      -0.827      0.116
    0.116
             333.000       0.997      -0.886       1.531    8.11%       0.588      1.060
     ZFINLIT               0.000      -0.232      -1.831   11.41%      -0.754      0.324
    0.324
             333.000       0.997      -0.798       1.401   21.02%       0.324      1.401
     ZWRKHRS               0.000       0.457      -1.436   11.41%      -0.908     -0.381
   -0.117
             333.000       0.997      -0.254       3.497    0.30%       0.173      0.806
     ZHEDU                 0.000      -0.331      -1.727   15.32%      -0.702      0.323
    0.323
             333.000       0.997      -0.861       1.348   21.32%       0.323      1.348


THE MODEL ESTIMATION TERMINATED NORMALLY



MODEL FIT INFORMATION

Number of Free Parameters                       23

Loglikelihood

          H0 Value                       -1797.481
          H0 Scaling Correction Factor      0.9313
            for MLR

Information Criteria

          Akaike (AIC)                    3640.962
          Bayesian (BIC)                  3728.549
          Sample-Size Adjusted BIC        3655.592
            (n* = (n + 2) / 24)



FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THE ESTIMATED MODEL

    Latent
   Classes

       1         61.39987          0.18438
       2         68.77599          0.20653
       3        140.07128          0.42063
       4         62.75286          0.18845


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
```

BASED ON ESTIMATED POSTERIOR PROBABILITIES

Latent Classes		
1	61.39987	0.18438
2	68.77599	0.20653
3	140.07128	0.42063
4	62.75286	0.18845

FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THEIR MOST LIKELY LATENT CLASS MEMBERSHIP

Class Counts and Proportions

Latent Classes		
1	63	0.18919
2	69	0.20721
3	139	0.41742
4	62	0.18619

CLASSIFICATION QUALITY

Entropy 0.920

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row)
by Latent Class (Column)

	1	2	3	4
1	0.969	0.000	0.000	0.031
2	0.000	0.963	0.037	0.000
3	0.000	0.017	0.978	0.005
4	0.006	0.000	0.025	0.969

Classification Probabilities for the Most Likely Latent Class Membership (Column)
by Latent Class (Row)

	1	2	3	4
1	0.994	0.000	0.000	0.006
2	0.000	0.966	0.034	0.000
3	0.000	0.018	0.970	0.011
4	0.031	0.000	0.012	0.957

Logits for the Classification Probabilities for the Most Likely Latent Class Membership (C
olumn)
by Latent Class (Row)

	1	2	3	4
1	5.089	-8.721	-8.721	0.000
2	0.000	13.781	10.436	0.000
3	-9.324	0.492	4.462	0.000
4	-3.414	-13.772	-4.421	0.000

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MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Latent Class 1				
Means				
ZFINSUP	-1.619	0.031	-52.838	0.000
ZFINLIT	-0.199	0.114	-1.747	0.081
ZWRKHRS	0.455	0.143	3.191	0.001
ZHEDU	-0.510	0.143	-3.575	0.000
Variances				
ZFINSUP	0.065	0.004	18.513	0.000
ZFINLIT	0.982	0.060	16.476	0.000
ZWRKHRS	0.869	0.069	12.594	0.000
ZHEDU	0.921	0.058	15.844	0.000
Latent Class 2				
Means				
ZFINSUP	1.229	0.036	33.711	0.000
ZFINLIT	0.059	0.134	0.440	0.660
ZWRKHRS	-0.635	0.096	-6.644	0.000
ZHEDU	-0.129	0.114	-1.128	0.259
Variances				
ZFINSUP	0.065	0.004	18.513	0.000
ZFINLIT	0.982	0.060	16.476	0.000
ZWRKHRS	0.869	0.069	12.594	0.000
ZHEDU	0.921	0.058	15.844	0.000
Latent Class 3				
Means				
ZFINSUP	0.386	0.026	15.029	0.000
ZFINLIT	0.109	0.088	1.241	0.215
ZWRKHRS	0.032	0.085	0.372	0.710
ZHEDU	0.186	0.084	2.212	0.027
Variances				
ZFINSUP	0.065	0.004	18.513	0.000
ZFINLIT	0.982	0.060	16.476	0.000
ZWRKHRS	0.869	0.069	12.594	0.000
ZHEDU	0.921	0.058	15.844	0.000
Latent Class 4				
Means				
ZFINSUP	-0.625	0.045	-14.012	0.000
ZFINLIT	-0.111	0.130	-0.855	0.393
ZWRKHRS	0.179	0.110	1.629	0.103
ZHEDU	0.225	0.119	1.892	0.058
Variances				
ZFINSUP	0.065	0.004	18.513	0.000
ZFINLIT	0.982	0.060	16.476	0.000
ZWRKHRS	0.869	0.069	12.594	0.000
ZHEDU	0.921	0.058	15.844	0.000

Categorical Latent Variables

Means

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```
    CLASS#1           -0.022      0.192     -0.114      0.909
    CLASS#2            0.092      0.184      0.499      0.618
    CLASS#3            0.803      0.160      5.032      0.000


QUALITY OF NUMERICAL RESULTS

     Condition Number for the Information Matrix              0.850E-03
       (ratio of smallest to largest eigenvalue)


EQUALITY TESTS OF MEANS ACROSS CLASSES USING THE BCH PROCEDURE
WITH 3 DEGREE(S) OF FREEDOM FOR THE OVERALL TEST

FINBEH
                          Mean       S.E.                            Mean       S.E.

  Class 1                3.314      0.124  Class 2                  2.290      0.131
  Class 3                3.116      0.084  Class 4                  3.114      0.123

                    Chi-Square     P-Value                     Chi-Square     P-Value

  Overall test          38.384      0.000  Class 1 vs. 2           32.374      0.000
  Class 1 vs. 3          1.750      0.186  Class 1 vs. 4            1.264      0.261
  Class 2 vs. 3         27.205      0.000  Class 2 vs. 4           21.143      0.000
  Class 3 vs. 4          0.000      0.987


DIAGRAM INFORMATION

  Mplus diagrams are currently not available for Mixture analysis.
  No diagram output was produced.


     Beginning Time:  19:44:05
        Ending Time:  19:44:05
       Elapsed Time:  00:00:00


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